

Joint inversion of seismic AVO and EM data for gas saturation estimation using a sampling-based stochastic model

Jinsong Chen*, G. Michael Hoversten, and D. W. Vasco, Lawrence Berkeley National Laboratory
Yoram Rubin and Zhangshuan Hou, University of California at Berkeley

Summary

A stochastic model is developed to estimate gas saturation and porosity using seismic AVO and EM data. Markov chain Monte Carlo (MCMC) sampling methods are used to obtain posterior probability density functions of unknown parameters constrained by seismic AVO and EM data and prior information. Unlike conventional inverse methods, which search for an optimal solution giving the smallest misfit, MCMC methods estimate probability density functions of unknown gas saturation and porosity. This allows for evaluation of uncertainty as well as estimation of those parameters. A synthetic study, typical of gas exploration in the deep water of the Gulf of Mexico, is developed to demonstrate the benefits of joint inversion of seismic AVO and EM data. Results show that the inclusion of EM data reduces the uncertainty and ambiguity in gas saturation and porosity estimation.

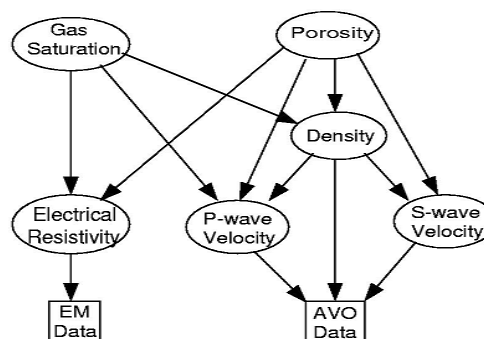
Introduction

Exploring economic gas resources in the deep water of the Gulf of Mexico (GOM) is very difficult. Widely used seismic imaging techniques (such as seismic AVO) can provide detailed information about geological structures and units that contain hydrocarbon gas, but cannot discriminate between non-economic and economic gas concentrations due to the insensitivity of seismic velocity and density to gas saturation. Marine electromagnetic (EM) methods have the ability to discriminate between non-economic and economic gas saturation because electrical resistivity of reservoir materials is highly sensitive to gas saturation (through the water saturation), as evidenced by Archie's Law (Archie, 1942). However, inversion of EM data only is subject to a large degree of uncertainty since porosity and geological units are not well defined. Furthermore, the vertical resolution of EM data is generally poorer than the associated seismic resolution.

Since seismic AVO and EM data provide complementary information for determining rock physical and reservoir parameters, joint inversion of those data may have advantages over the inversion of the individual data sets. Figure 1 is a schematic map showing relationships among reservoir parameters (porosity and gas saturation), acoustical properties (velocity and density), electrical properties (resistivity), and seismic AVO and EM data. Since both gas

saturation and porosity are related to seismic AVO and EM data, we hypothesize that joint inversion of seismic AVO and EM data will provide better estimates of gas saturation and porosity than using each data type in isolation.

In this study, we test our hypothesis using a sampling-based stochastic model, based on a typical situation of gas exploration in the Gulf of Mexico. In this preliminary study, we make the following assumptions: (1) both seismic AVO and EM data are obtained from one-dimensional (or layered) models, (2) the thickness and electrical resistivity of the overburden are known, and (3) rock physical models for linking different types of parameters are known. In a future study, we will extend our methodology to the case where EM data are obtained from a two- or three-dimensional forward model. We will also investigate the effects of uncertainty in



overburden and in rock physical models.

Figure 1: Relationships between reservoir parameters and geophysical attributes.

Method

Stochastic Model

We consider layered (or one-dimensional) models for both seismic AVO and EM surveys. Suppose we have collected seismic AVO data (reflectivity) from several incident angles, and marine EM data (electrical field) from different offsets using several frequencies. Since the goal of this study is to estimate gas saturation within a given depth interval (target zone), we assume the thickness and electrical resistivity of

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overburden are obtained from other sources of information. The effects of overburden on gas saturation estimation will be investigated in a future study. We also assume that the reservoir does not contain oil in the current model, which will be included in the final model.

Let ϕ_i and S_{gi} represent porosity and gas saturation in layer- i . Let \mathbf{R} and \mathbf{E} represent seismic AVO and EM data. Let τ_r and τ_e represent the inverse variances of the measurement errors of seismic AVO and EM data. According to the Bayes' theorem (Rubin, 2003), the stochastic model is given by:

$$f(\{\phi_i\}, \{S_{gi}\}, \tau_r, \tau_e | \mathbf{R}, \mathbf{E}) \propto f(\{\phi_i\}, \{S_{gi}\}, \tau_r, \tau_e) f(\mathbf{R}, \mathbf{E} | \{\phi_i\}, \{S_{gi}\}, \tau_r, \tau_e). \quad (1)$$

The first term at the right side of Equation 1 is referred to as the likelihood function, which is the link between the seismic AVO and EM data and the unknown porosity and gas saturation. The second term is the prior distribution of the unknown parameters, which is obtained from other sources of information. Equation 1 defines a joint posterior probability distribution function. Our goal is to obtain the marginal posterior distribution function of each unknown parameter from the joint distribution.

Likelihood Model

Since seismic AVO and EM data are different types of geophysical measurements of subsurface properties, we assume they are independent of each other. Therefore, we can simplify the likelihood function shown in Equation 1 as follows:

$$f(\mathbf{R}, \mathbf{E} | \{\phi_i\}, \{S_{gi}\}, \tau_r, \tau_e) \propto f(\mathbf{R} | \{\phi_i\}, \{S_{gi}\}, \tau_r) f(\mathbf{E} | \{\phi_i\}, \{S_{gi}\}, \tau_e) \quad (2)$$

Each term on the right side of the above equation is obtained using its corresponding forward model.

Seismic AVO data are direct functions of seismic P- and S-wave velocities and bulk density (Mavko et al., 1998). All the parameters are related to gas saturation and porosity through rock physical relations (Figure 1). Consequently, we can write the AVO data as:

$$\mathbf{R} = M_r(\{\phi_i\}, \{S_{gi}\}) + \boldsymbol{\varepsilon}_r, \quad (3)$$

where vector $\boldsymbol{\varepsilon}_r$ is the measurement error of AVO data. We assume the measurement error is normally distributed with zero mean and an inverse covariance matrix of $\tau_r \mathbf{I}_m$, here \mathbf{I}_m is the m -dimensional identity matrix and m is the total number of AVO data. Similarly, we can determine the likelihood function of EM data. Since EM data span several orders of magnitude, we use relative errors instead of absolute errors. The likelihood function of EM data can be written as follows:

$$\mathbf{E} = M_e(\{\phi_i\}, \{S_{gi}\}) + \boldsymbol{\varepsilon}_e M_e(\{\phi_i\}, \{S_{gi}\}). \quad (4)$$

Vector $\boldsymbol{\varepsilon}_e$ is the relative error of EM data, which is assumed to be normally distributed with zero mean and an inverse covariance of $\tau_e \mathbf{I}_n$, where \mathbf{I}_n is the n -dimensional identity matrix and n is the number of EM data.

Prior Model

The prior distribution function in Equation 1 summarizes the information not included in the likelihood functions. In this study, we make the following assumptions: (1) measurement errors of seismic AVO and EM data are independent of gas saturation and porosity, (2) gas saturation and porosity at each layer are independent of each other, and (3) gas saturation at each layer is uniformly distributed on [0,1] and porosity is uniformly distributed on [0, 0.35]. The above assumptions are physically justified for reservoirs in the deep water of the Gulf of Mexico.

Sampling Method

The method for obtaining the marginal posterior distribution function of each unknown parameter is key to the success of the stochastic model. Since forward models of seismic AVO and EM data are highly nonlinear and the number of unknown parameters is large, conventional analytical methods are limited. We use a Markov Chain Monte Carlo (MCMC) sampling method to obtain many realizations of each marginal posterior distribution function. MCMC methods are a powerful tool for dealing with complicated statistical models involving a large number of dependent variables (Gilks et al., 1996). Using those samples, we can make inferences on each unknown parameter, such as its mean, variance, and probability density function.

We adopt three methods to speed up the MCMC sampling process. Firstly, we construct transformations of both gas saturation and porosity using the logistic function. Secondly, we apply a mixing algorithm (Tierney, 1994), which includes independent sampling, Gaussian random walk, antithetic variable methods, and random shuffling. Finally, we use the Metropolis-coupled MCMC method to run several chains to improve the mixing. By using those techniques, we are able to obtain many samples following a relatively short burn-in stage.

Synthetic Study

Our goal in this study is to demonstrate the benefits of combining EM and seismic AVO data for gas saturation estimation. Here we shall consider a layered model, where

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the sea floor is 1000m under the water surface and the overburden is 2000m under the sea floor. Five layers lie beneath the overburden. The thickness of each layer is 30m. The gas saturation of the true model is 0.05, 0.95, 0.4, 0.9, and 0.1, respectively, from the upper layer to the bottom layer, and the porosity of the true model is 0.15, 0.25, 0.15, 0.1, and 0.05, respectively.

The synthetic data include seismic AVO data from five offsets (incident angles 0, 10, 20, 30, and 40 degrees) and marine EM data using five different frequencies (0.1, 0.25, 0.5, 1.0, and 2.0 Hz) from six offsets (source-to-receiver distances 4, 5, 6, 7, 9 and 10 km). Thirty percent Gaussian random noises are added to the true AVO data and fifteen percent random noises to the true EM data. We use the rock physics models described by Hoversten et al (2003) to link gas saturation and porosity to seismic velocity, bulk density, and electrical resistivity.

We first estimate gas saturation and porosity using seismic AVO data only. The estimated probability density functions of gas saturation and porosity at five layers are shown in Figures 2 and 3 as red dashed lines. From those figures, we can see that the seismic AVO data provide good estimates of porosity in the first four layers, but a poor estimate at layer 5. This is because the last layer is poorly constrained by the data as compared to other layers. Seismic AVO data is less sensitive to the distribution of gas saturation. Although the modes of the first three layers are close to their corresponding true values, the uncertainty is rather large. In addition, seismic data almost provide no information about gas saturation in the last two layers.

The estimated probability density functions of gas saturation and porosity using both seismic AVO and EM data are shown in Figures 2 and 3 as black solid lines. From the comparison between the estimates obtained from seismic AVO data only and from the joint inversion, we can see that EM data significantly reduce the uncertainty associated with estimates of gas saturation in the first three layers, and successfully identify the high gas saturation in layer 4 and the low gas saturation in layer 5. Also note that EM data reduce the uncertainty associated with the porosity estimates in all the five layers.

Conclusions

We have developed a sampling-based stochastic model for estimating gas saturation and porosity, and applied the methodology to investigate the usefulness of combining EM and seismic AVO data for gas saturation and porosity estimation. The developed model provides the estimated

probability density function rather than a single optimal solution of each unknown variable. This allows us to fully characterize the unknown variable, such as its mean, variance, mode, range, and even various predictive intervals.

The synthetic study based on the layered model has shown that the incorporation of EM data into gas saturation and porosity estimation significantly reduces the uncertainty in both gas saturation and porosity estimation. Most importantly, EM data can help to successfully identify high gas concentrations in the deep layer, which is not possible when using only seismic AVO data.

We have made several assumptions in this preliminary study. These assumptions may affect the accuracy of gas saturation and porosity estimation. For example, the electrical resistivity of the overburden was assumed to be known and uncertainty in rock physical models was not considered. We will explore those effects in a future study. We will also extend our approach to two- or three-dimensional forward models.

Acknowledgements

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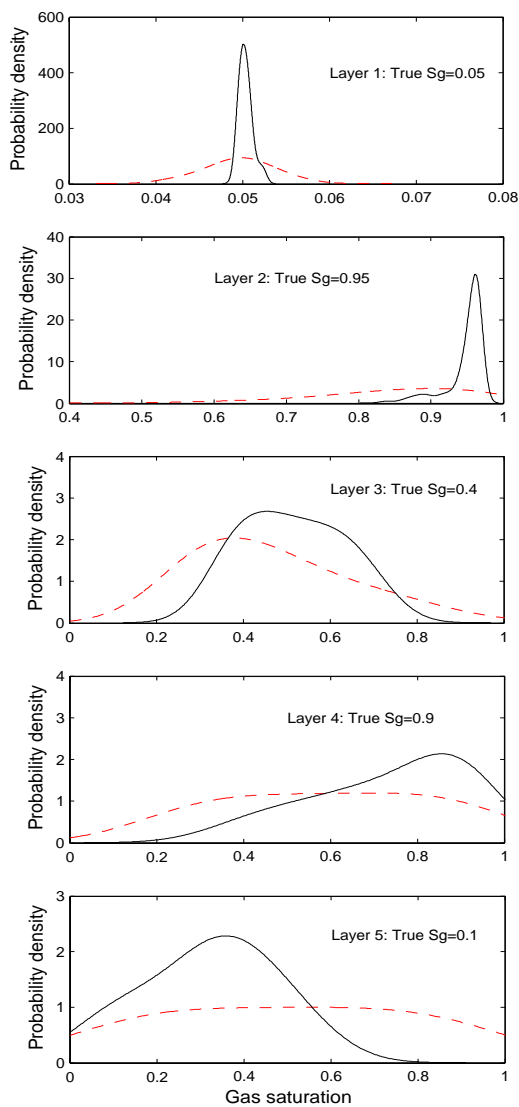


Figure 2: Comparison of estimated gas saturation (Red dashed lines: using seismic AVO data only, and black solid lines: using both seismic AVO and EM data)

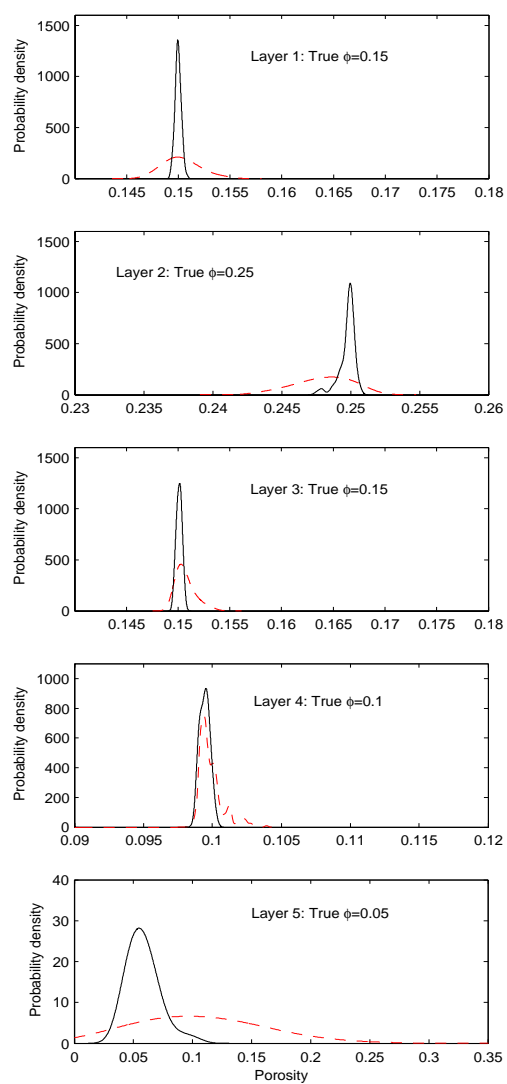


Figure 3: Comparison of estimated porosity (Red dashed lines: using seismic AVO data only, and black solid lines: using both seismic AVO and EM data)